Integration of Language And Cognition at Pre-Conceptual Level

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Abstract–The paper discusses mathematical models of the mechanisms that the mind can use for combining language and cognition. I address the problem of concurrent language acquisition and conceptual learning. How a child can learn so fast? In concurrent learning of language and cognitive structures, language helps learning about objects in surrounding world and vice versa, which might explain why we can learn to recognize objects and words, but cannot remember a yellow page telephone book. The proposed theory addresses cognitive mechanisms of concepts, emotions, and goals and relates them to thought processes in which an event (in the outside world, or inside the mind) is understood as a concept. Learning language at the same time helps in this processes. The described framework can use various language models described in cognitive and computational linguistic literature, while avoiding combinatorial computational complexity that has been the nemesis of artificial intelligence and computational linguistics. The combinatorial complexity is avoided by using a new type of logic, dynamic logic, that unifies fuzzy logic and formal logic. The postulated mechanisms of integration of language and cognition at a pre-conceptual level, where conceptual and emotional contents are not differentiated might be interesting for theoretical linguistics and for practical development of understanding-based search engines.

Keywords: *cognition, linguistics, mind, symbols, dynamic logic, emotions, concepts, language acquisition, search engines*

1. LANGUAGE AND THE MIND

Language and thinking are distinctly human abilities. Close relationships between language and thinking encouraged equating these abilities in the past. Rule-based systems, using the mathematics of logic, implied significant similarities between the two. The situation has changed, in part due to the fact that logic-rule systems have not been sufficiently powerful to explain thinking, nor language abilities, and in part due to improved scientific understanding (psychological, cognitive, neural, linguistic) of the mechanisms involved. Among contemporary linguists there is a growing appreciation of a possibility that language and thinking could be distinct and different abilities of mind [see[1] for further references].

Human language mechanisms include abilities to acquire a large vocabulary, rules of grammar, and to use the finite set of words and rules to generate virtually infinite number of phrases and sentences [[2,3]]. Human thinking includes abilities to understand the surrounding world in terms of objects, their relationships (scenes and situations), relationships among relationships, and so on [[4]]. Researchers in computational linguistics, mathematics of intelligence and neural networks, cognitive science, neuro-physiology and psychology during the last twenty years significantly advanced understanding of the mechanisms of the mind involved in learning and using language, mechanisms of perception and cognition [[2,3,4,5,6,7]]. Much less advance was achieved toward deciphering mechanisms relating language acquisition and competence to learning, understanding and thinking about objective world. Although it seems clear that language and thinking are closely related abilities, intertwined in evolution, ontogenesis, and everyday use, still the currently understood mechanisms of language are mainly limited to relations of words to other words and phrases, but not to the objects in the surrounding world, not to cognition and thinking. Similarly, the role of language in cognition is not well understood. Possible mathematical approaches toward integrating language and thinking, words and objects, phrases and situations are discussed in this paper.

The paper starts with a mathematical description of thinking, which still is an issue of much controversy. Among researchers in mathematical intelligence it has become appreciated, especially during the last decades that thinking is not just a chain of logical inferences [[4,7]]. Yet, mathematical methods describing thinking as processes involving concepts, instincts, emotions, memory, imagination are not well known, although significant progress in this direction was achieved [[4,7]]. A brief historical overview of this area including difficulties and controversies is given in the next two sections from mathematical, psychological and neural standpoints; it is followed by a mathematical description of thinking processes. Then the paper discusses the ways in which the mathematical description of thinking can be combined with language, taking advantage of recent progress in computational linguistics. It touches upon novel ideas of computational semiotics relating language and thinking through signs and symbols. In conclusion, I briefly discuss relationships between mathematical, psychological, and neural descriptions of thinking processes and language as parts of the mind.

Words like *mind, thought, imagination, emotion, concept* are often used colloquially in many ways, but their use in science and especially in mathematics of intelligence has not been uniquely defined and is a subject of active research and ongoing debates [[7]]. According to a dictionary [[8]], mind includes conscious and unconscious processes, especially

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thought, perception, emotion, will, memory, and imagination, and it originates in brain. These constituent notions are discussed in [9] within the framework of .

A broad range of opinions exists on the mathematical methods suitable for the description of the mind. Founders of artificial intelligence thought that formal logic was sufficient [10] and no specific mathematical techniques would be needed to describe the mind [11]. An opposite point of view is that there are few specific mathematical constructs, "the first principles" of the mind organization. Among researchers taking this view is Grossberg, who suggested that the first principles include a resonant matching between lower-level signals [12] and higher-level representations and emotional evaluation of conceptual contents [13]; several researchers suggested specific principles of the mind organization [4,14,15,16]. Hameroff, Penrose, and the author (among others) considered quantum computational processes that might take place in the brain [17,18,19]. Although, it was suggested that new unknown yet physical phenomena will have to be accounted for explaining the working of the mind [18]. This paper describes mechanisms of the mind that can be "implemented" by classical-physics mechanisms of the brain neural networks and, alternatively, by using existing computers.

2. Theories of the Mind, Combinatorial Complexity, and Logic

Understanding signals coming from sensory organs involves associating subsets of signals corresponding to particular objects with internal representations of these objects. This leads to recognition of the objects and activates internal brain signals leading to mental and behavioral responses, which constitute the understanding of the meaning (of the objects).

Developing mathematical descriptions of the very first *recognition* step of this seemingly simple association-recognition-understanding process has not been easy, a number of difficulties have been encountered during the past fifty years. These difficulties have been summarized under the notion of combinatorial complexity (CC) [20]. The problem was first identified in pattern recognition and classification problems in the 1960s and was named "the curse of dimensionality" [21]. The CC persisted through logic-rule-based systems and the first Chomsky ideas concerning mechanisms of language grammar related to deep structure [22], which were also based on a similar idea of logical rules; it continue to plague model-based systems and the similar second Chomsky idea of *rules and parameters* [23]. The CC became a ubiquitous feature of intelligent algorithms and seemingly, a fundamental mathematical limitation.

Combinatorial complexity has been related to the type of logic, underlying various algorithms and neural networks [20]. Formal logic is based on the "law of excluded third", according to which every statement is either true or false and nothing in between. Therefore, algorithms based on formal logic have to evaluate every little variation in data or internal representations as a separate logical statement; a large number of combinations of these variations cause combinatorial complexity. In fact, combinatorial complexity of algorithms based on logic has been related to the Gödel theory: it is a finite system manifestation of the incompleteness of logic [24]. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third [25]. Yet the mathematics of multivalued logic is no different in principle from formal logic. Fuzzy logic encountered a difficulty related to the degree of fuzziness: if too much fuzziness is specified, the solution does not achieve a needed accuracy, if too little, it becomes similar to formal logic.

3. Mind: Concepts and Emotions

Let me summarize briefly and in a much simplified way several aspects of the working of the mind, which seem essential to the development of the mathematical descriptions of the mind mechanisms: instincts, concepts, emotions, behavior generation. The mind has evolved for the purpose of survival and therefore it serves for a better satisfaction of the basic instincts, which have emerged as survival mechanisms even before the mind. Instincts operate like internal sensors: for example, when a sugar level in blood goes below a certain level an instinct "tells us" to eat. The most accessible to our consciousness mechanism of the mind is concepts: the mind operates with concepts. Concepts are like internal models of the objects and situations; this analogy is quite literal, e.g., during visual perception of an object, an internal concept-model project an image onto the visual cortex, which is matched there to an image projected from retina (this simplified description will be refined later). An ability for concepts evolved for instinct satisfaction, and the mechanism linking concepts and instincts involves emotions. Emotions are neural signals connecting instinctual and conceptual brain regions. Whereas in colloquial usage, emotions are often understood as facial expressions, higher voice pitch, exaggerated gesticulation, these are the outward signs of emotions, serving for communication. A more fundamental role of emotions within the mind system is that emotional signals evaluate concepts for the purpose of instinct satisfaction. This evaluation is not according to rules or concepts (like in rule-systems of artificial intelligence), but according to a different instinctual-emotional mechanism of dynamic logic described in the next section. This emotional mechanism of dynamic logic is crucial for breaking out of the "vicious circle" of combinatorial complexity.

The results of conceptual-emotional understanding of the world are actions (or behavior) in the outside world or within the mind. In this paper we touch on only one type of behavior, the behavior of improving understanding and knowledge of the language and world. In the next section we describe a mathematical theory of a "simple" conceptual-emotional recognition and understanding. In addition to concepts and emotions, it involves with necessity

mechanisms of intuition, imagination, conscious, unconscious, and aesthetic emotion.[26] And this process is intimately connected to an ability of mind to form symbols and interpret signs.

The mind involves a hierarchy of multiple levels of concept-models, from simple perceptual elements (like edges, or moving dots), to concept-models of objects, to complex scenes, and up the hierarchy... toward the concept-models of the meaning of life and purpose of our existence. Hence the tremendous complexity of the mind, yet relatively few basic principles of the mind organization go a long way explaining this system.

4. MODELING FIELD THEORY (MFT)

Modeling field theory [[4]], summarized below, associates lower-level signals with higher-level concept-models (or internal representations), resulting in understanding of signals, while overcoming the difficulties of CC described in Section 2. It is achieved by using measures of similarity between the concept-models and the input signals combined with a new type of logic the fuzzy dynamic logic. Modeling field theory is a multi-level, hetero-hierarchical system. This section describes a basic mechanism of interaction between two adjacent hierarchical levels of signals (fields of neural activation); sometimes, it will be more convenient to talk about these two signal-levels as an input to and output from a (single) processing-level.

At each level, the output signals are concepts recognized (or formed) in input signals. Input signals **X** are associated with (or recognized, or grouped into) concepts according to the representations-models and similarity measures at this level. In the process of association-recognition, models are adapted for better representation of the input signals; and similarity measures are adapted so that their fuzziness is matched to the model uncertainty. The initial uncertainty of models is high and so is the fuzziness of the similarity measure; in the process of learning models become more accurate and the similarity more crisp, the value of the similarity measure increases; this is the essence of dynamic logic.

Internal Models, Learning, and Knowledge Instinct

During the learning process, new associations of input signals are formed resulting in evolution of new concepts. Input signals $\{\mathbf{X}(n)\}$, is a field of input neuronal synapse activation levels, n = 1,... N, enumerates the input neurons and $\mathbf{X}(n)$ are the activation levels; a set of concept-models h = 1,... H, is characterized by the models (representations) $\{\mathbf{M}_h(n)\}$ of the signals $\mathbf{X}(n)$; each model depends on its parameters $\{\mathbf{S}_h\}$, $\mathbf{M}_h(\mathbf{S}_h,n)$. In a highly simplified description of a visual cortex, n enumerates the visual cortex neurons, $\mathbf{X}(n)$ are the "bottom-up" activation levels of these neurons coming from the retina through visual nerve, and $\mathbf{M}_h(n)$ are the "top-down" activation levels (or priming) of the visual cortex neurons from previously learned object-models[27]. Learning process attempts to "match" these top-down and bottom-up activations by selecting "best" models and their parameters. Mathematically, learning increases a similarity measure between the sets of models and signals, $L(\{\mathbf{X}(n)\},\{\mathbf{M}_h(n)\})$. The similarity measure is a function of model parameters and associations between the input synapses and concepts-models. It is constructed in such a way that any of a large number of objects can be recognized, it treats each concept-model as an alternative for each subset of signals

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n\in N} \sum_{h\in H} r(h)\, l(\mathbf{X}(n) \mid \mathbf{M}_h(n)); \tag{1}$$

here, $l(\mathbf{X}(n)|\mathbf{M}_h(n))$ (or simply $l(n|h)$) is a conditional partial similarity between one signal $\mathbf{X}(n)$ and one model $\mathbf{M}_h(n)$, and all possible combinations of signals and models are accounted for in this expression. Parameters r(h) are proportional to the number of signals {n} associated with the model h. Maximization of the similarity measure (1) is a mathematical representation of the knowledge instinct, the drive to improve knowledge, to improve the similarity between the internal models-representations and surrounding world (as sensed through the sensory organs).

The dynamic logic algorithm accomplishing this maximization without combinatorial complexity is described in[[4],[26]]. During this maximization process initial fuzzy and uncertain models are associated with structures in the input signals, fuzzy models are getting more definite and crisp. The type, shape and number of models are selected so that the internal representation within the system is similar to input signals: the MF concept-models represent structure-objects in the input signals. Mathematical equations describing this process I call fuzzy dynamic logic, and in terms of processes in the mind, it describes an elementary thinking process involving instincts, imagination, emotions and concepts[26].

A multi-level hierarchical language MFT system can be developed by adding more levels similar to a word-phrase level described in section 4.3. Relatively simple "bag" models can be used for each layer, or realistic language models of phonemes, word-sounds, sentences, paragraphs and large bodies of texts can be utilized [[28,29]]. Among many possible commercial applications of such systems could be understanding-based search engines; everybody familiar with the frustration of the web searches, would appreciate a search engine that even remotely understands user queries and contents of the web pages.

Integrating Language and Thinking

During visual perception, internal representations-models are matched in the visual cortex to retinal signals, cortex representations maintain their spatial topology and continuity. A number of MFT models have been developed for visual perception, for other sensor modalities, and for cognition of simple situations [[4]]. By using concept-models

with multiple sensor modalities, a MFT system can integrate signals from multiple sensors, while adapting and improving internal concept-models. Similarly, MFT can be used to integrate language and thinking. This requires the development of language MFT models. Here, I briefly outline an approach to the development of MFT language models. Language, like MFT is a hierarchical system, it involves sounds, phonemes, words, phrases, sentences, grammar... and each level operates with its own models. Like other models of mind, these models are results of evolution; for computational intelligent systems we have to develop them, and this development at each level is a research project, which is added by a number of already described language models [2,3,5,30]. Knowledge instinct described above as a drive for cognition, 'becomes' language instinct that drives language acquisition.

The presentation illustrates an approach to the development of models of phrases from words for the purpose of text understanding; that could be used, for example, for an understanding-based search engine. The input data, $\mathbf{X2}(n)$, in this "phrase-level" MF system, are word strings, for simplicity, of a fixed length, S, $\mathbf{X2}(n) = \{ w_{n+1}, w_{n+2} \dots w_{n+S} \}$. Here w_n are words from a given dictionary of size K, $W = \{w_1, w_2 \dots w_K\}$, and *n* is the word position in a body of texts. Language models $\{\mathbf{M2}_{h2}(n)\}$ are representations of these data, similar to cognitive models being representations of sensory signals. A simple phrase model could be "a bag of word", that is, a subset of words from a dictionary, without any order or rules of grammar, alternatively more complicated models can be used that model known structures of natural languages [2,3,5,6,30,31]. The presentation illustrates an example of bag-model and dynamic logic algorithm that leads to efficient (non-combinatorial) learning of the **M2** model contents.

Integration of language and cognition in MFT is attained by characterizing objects and situations in the world with two types of models, language models considered above and cognitive models considered previously and in [4], so that conditional partial similarities are modified as follows

$$l(\mathbf{X}(n)|\mathbf{M}_h(n)) \quad l(\{\mathbf{X1}(n),\mathbf{X2}(n2)\}|\{\mathbf{M1}_{h1}(n),\mathbf{M2}_{h2}(n)\}); \quad (2)$$

Here $\{\mathbf{X1}(n), \mathbf{X2}(n)\}$ is a pair of strings of concurrent (signals, words), n enumerates all situations; sometimes either sensory signals or words are present, but not both, so either **X1** or **X2** are empty, but often both are present, like when immediately occurring situations are discussed. Similarly, $\{\mathbf{M1}_{h1}(n), \mathbf{M2}_{h2}(n)\}$ is a pair of (cognitive, phrase)-models.

Integrated MFT system learns similarly to human, in parallel in three realms: (1) language models can be learned to some extent independently from cognition, when language data are encountered for the first time with limited or no association with perception and cognition (like in a newborn baby); (2) similarly, cognitive models can be learned to some extent independently from language, when perception signal data are encountered for the first time in limited or no association with language data; and (3) language and cognitive models are learned jointly, when language data are present in some association with perception signals, like during mother talking to a baby: "this is a car" (perception-models and word-models), and like during more complicated conversations: "Look at Peter and Ann, they are in love" (cognitive-models and phrase-models).

The original, inborn cognitive and language models are fuzzy structures equally and poorly matching any sensory or language data. In the process of learning model fuzziness decreases, they become crisp models associated with specific situations and phrases, and cognitive models get associated with language models. Because the integrated (cognitive, language)-model structures (2) are inborn, association between language and cognition begins at a "pre-conceptual" fuzzy level, inaccessible to consciousness. Also, a large number of language models formed in early childhood facilitate learning of corresponding cognitive models throughout later life, similarly, cognitive (say visual) models facilitate learning of language models.

5. Thinking Process and Semiotics

Semiotics studies signs and symbols [32,33]. The essence of a sign is that it can be interpreted by an intelligent system to refer to something else. Whereas some semiotic literature uses words sign and symbol inconsistently, I call *symbol a process of sign interpretation.* In mathematics and in "Symbolic AI" there is no difference between signs and symbols. Both are considered as notations, arbitrary non-adaptive entities with axiomatically fixed meaning. This non-differentiation is a "hangover" from an old superstition that logic describes mind, a direction in mathematics and logical philosophy that can be traced through the works of Frege, Hilbert, Russell, to its bitter end in Gödel theory, and its revival during the 1960s and 1970s in artificial intelligence. In general culture, symbols are understood as psychological processes of sign interpretation. Jung emphasized that symbol-processes connect conscious and unconscious [34], Pribram wrote of symbols as adaptive, context-sensitive signals in the brain, whereas signs he identified with less adaptive and relatively context-insensitive neural signals [35].

A symbol-process of a sign interpretation coincides with an elementary thought-process [26]. Each sign-interpretation or elementary thought process, a symbol, involves conscious and unconscious, emotions, concepts, and behavior; this definition connecting symbols to archetypes (fuzzy unconscious model-concepts) corresponds to a usage in general culture and psychology. As described previously, this process continues up and up the hierarchy of models and mind toward the most general models. In semiotics this process is called *semiosis*, a continuous process of creating and interpreting the world outside (and inside our mind) as an infinite hierarchical stream of signs and symbol-processes.

6. Conclusion

A modeling field system described in this paper integrates language and cognitive abilities. The integration occurs at a pre-conceptual level of fuzzy models, which might provide a basis for the understanding of complex interaction between abilities for language and cognition. Pre-conceptual, fuzzy inborn structures are unconscious and do not differentiate between conceptual and emotional content. This might point toward an intriguing Humboldt's hypothesis about creative "inner form" of language [[36]]. It might provide a basis for understanding differences between highly conceptual, differentiated, instrumental recent forms of language and older, less differentiated, more cumbersome, yet more synthetic and more creative forms of language. Practical utilization could be for the development of understanding-based search engines. I hope this development will be useful for theoretical linguistics, computational linguistics, and engineering.

REFERENCES

[1] Pinker, S. (2000). The Language Instinct: How the Mind Creates Language. Harper Perennial.

[2] Jackendoff, R. (2002). Foundations of Language: Brain, Meaning, Grammar, Evolution. Oxford University Press, New York, NY.

[3] Pinker, S. (2000). Words and Rules: The Ingredients of Language Harper Perennial.

[4] Perlovsky, L.I. (2001). Neural Networks and Intellect: using model-based concepts. Oxford University Press, New York, NY.

[5] Rieger, B.B., ed. (1981). Empirical Semantics II. A Collection of New Approaches in the Field. Quantitative Linguistics, v. 13, Brockmeyer, Bochum, Germany.

[6] Mehler,A. (2002). Components of a Model of Context-Sensitive Hypertexts. In: Journal of Universal Computer Science (J.UCS) 8(10), 924-943.

[7] For the discussions and further references see: Grossberg, S. (1988). *Neural Networks and Natural Intelligence.* MIT Press, Cambridge, MA. Meystel, A.M., Albus, J.S. (2001). *Intelligent Systems: Architecture, Design, and Control.* Wiley, New York; also[4].

[8] The American Heritage College Dictionary, Houghton Mifflin, 3rd ed., 2000, Boston, MA.

[9] Perlovsky, L.I. (2003). Higher Spiritual Abilities (Prolegomena To A Physical Theory). Integration of Knowledge Intensive Multi-Agent Systems conference, KIMAS'03, Cambridge,MA

[10] Newell, A. (1983). Intellectual issues in the history of artificial intelligence. In The study of information, ed. F.Machlup & U.Mansfield, J.Wiley, New York, NY.

[11] Minsky, M. (1988). The Society of Mind. MIT Press, Cambridge, MA.

[12] Grossberg, S. (1988). *Neural Networks and Natural Intelligence.* MIT Press, Cambridge, MA.

[13] Grossberg, S. & Levine, D.S. (1987). Neural dynamics of attentionally modulated Pavlovian conditioning: blocking, inter-stimulus interval, and secondary reinforcement. *Psychobiology*, **15**(3), pp.195-240;

[14] Josephson, B.D. (1997). *An integrated theory of nervous system functioning embracing nativism and constructivism.* International Complex Systems Conference, Nashua, NH, USA, September 21-26, 1997.

[15] Zadeh, L.A. (1997). *Information granulation and its centrality in human and machine intelligence.* Proceedings of the Conf. on Intelligent Systems and Semiotics '97. Gaithersburg, MD, pp. 26-30.

[16] Meystel, A. (1995). Semiotic Modeling and Situational Analysis. AdRem, Bala Cynwyd, PA.

[17] Hameroff, S.R. (1994). *Toward a Scientific Basis for Consciousness.* MIT Press, Cambridge, MA.

[18] Penrose, R. (1994). *Shadows of the Mind.* Oxford University Press, Oxford, England.

[19] Perlovsky, L.I. (1997). Towards Quantum Field Theory of Symbol. Proceedings of the Conference on Intelligent Systems and Semiotics '97. Gaithersburg, MD, pp. 295-300.

[20] Perlovsky, L.I. (1998). Conundrum of Combinatorial Complexity. IEEE Trans. PAMI, **20**(6) pp. 666-670.

[21] Bellman, R.E. (1961). *Adaptive Control Processes.* Princeton University Press, Princeton, NJ.

[22] Chomsky, N. (1972). *Language and Mind.* Harcourt Brace Javanovich, New York, NY.

[23] Chomsky, N. (1981). *Principles and Parameters in Syntactic Theory.* In N.Hornstein and D.Lightfoot (eds), 1981, *Explanation in Linguistics. The Logical Problem of Language Acquisition*, Longman, London

[24] Perlovsky, L.I. (1996). *Gödel Theorem and Semiotics.* Proceedings of the Conference on Intelligent Systems and Semiotics '96. Gaithersburg, MD, v.2, pp. 14-18.

[25] Jang,J.-S.R., Sun,C.-T., and Mizutani, E. (1996). Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice Hall, Upper Saddle River, NJ.

[26] Perlovsky, L.I. (2003). *Higher Spiritual Abilities (Prolegomena To A Physical Theory).* Integration of Knowledge Intensive Multi-Agent Systems conference, KIMAS'03, Cambridge,MA.

[27] In fact there are many levels between the retina, visual cortex, and object-models.

[28] Rieger, B.B. (1995). Situational semantics and computational linguistics: towards informational ecology. In Kornwachs & Jacoby eds., Information. New questions to a multidisciplinary concept. Berlin, Academie, Germany.

[29] Mehler, A. (1996). A multiresolutional approach to fuzzy text meaning. Intelligent systems: a semiotic perspective. Proc. 1996 Int. Multidisciplinary Conf. V.1., pp.261-273.

[30] Mehler, A. (2002). Hierarchical Orderings of Textual Units. Proceedings of the 19th International Conference on Computational Linguistics, COLING 2002, Taipei. San Francisco: Morgan Kaufmann, 646-652.

[31] Rieger, B.B. (1998). Tree-like dispositinal dependency structures for non-propositional semantic inferencing: n a SCIP upproachto natural language understanding by machine. In Bouchon-Meunier and Yager, eds., *Proc. 7th Int. Conf. On Information Processing and Management of*

Uncertainty in Knowledge-based Systems (IPMU-198), Paris, pp.351-358.

[32] Sebeok, T.A. 1995, *Sign: An Introduction to Semiotics.* Univ. Toronto Press, Toronto, Canada.

[33] Peirce, C.S. (1935-66). *Collected Papers of Charles Sanders Peirce.* Harvard Univ. Press., Cambridge, MA; Morris C. (1971). Writings on the General Theory of Signs, ed. Th. A. Sebeok. The Hague: Mouton.

[34] Jung, C.G. (1934). *Archetypes of the Collective Unconscious.* In the Collected Works, v.9,II, Bollingen Series XX, 1969, Princeton University Press, Princeton, NJ.

[35] Pribram,K. (1971). Languages of the Brain. Prentice Hall.

[36] von Humboldt, W. (1836). Humboldt: On Language: On the Diversity of Human Language Construction and its Influence on the Mental Development of the Human Species, ed. M. Losonsky , tr. P. Heath, 2nd ed. Cambridge Univ. Pr., 2000.